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An interval parameter conditional value-at-risk two-stage stochastic programming model for sustainable regional water allocation under different representative concentration pathways scenarios

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ABSTRACT

The shortage of water resources and the increasing competition among water users have highlighted the importance of the water allocation problem. Water availability is crucial for water resource allocation and changes frequently, leading to the necessity to predict available water. This paper develops a framework aimed to plan regional water allocations under different representative concentration pathways (RCP) scenarios using an interval parameter conditional value-at-risk (CVaR) two-stage stochastic programming model. This framework combines prediction and optimization to reflect climate change, the uncertainty of water system and the coordination between water resources allocation and risk. The feasibility and practicality of the framework are demonstrated by its application in a real-world case study in the Lower Songhua River Basin in northeast China. Comparison between the results of the developed model and actual conditions show that 11.61×10^8 m^3 volume of water supply can be saved after optimization, indicating that the developed model tends to allocate water in a more efficient way. The ratio of surface water to groundwater is reduced from 2:1 to 1.62:1. The proposed model has practical relevance for saving water and alleviating groundwater overexploitation. The approach is applicable to most areas with severe water shortages and groundwater overexploitation, and decision makers can determine the appropriate options for water resources allocation based on risk preferences and actual conditions.

1. Introduction

With the development of society and the expansion of cities, the unsustainable planning and management of regional water resources have intensified the imbalance between water supply and demand, resulting in a serious waste of surface water and severe exploitation of groundwater (Asefa et al., 2014; Fu et al., 2018a). In addition, extreme weather conditions influence the uncertainty of the available water supplies and lead to economic risk for water management systems, thus creating a barrier to the allocation of water resources (Hu et al., 2016a,b). Therefore, water allocation based on reasonable and available water prediction is an intense global issue.

The available surface water is a critical factor for regional water resources planning. Runoff is the main source of surface water and is influenced by uncertain climatic factors such as temperature and precipitation (Najafi and Moradkhani 2015; Milly et al., 2008). To quantify these uncertainties, many studies have coupled the representative concentration pathways (RCP) scenarios that were proposed in the Intergovernmental Panel on Climate Change Fifth Assessment Report (IPCC AR5) (Intergovernmental Panel on Climate Change (IPCC) 2013) with multiple general circulation models (GCMs) to predict the future climate. GCMs are considered the best available tools for modelling the future climate (Wang et al., 2017a,b). The variable infiltration capacity (VIC) model can simulate the available runoff. Zhang et al. (2012) used the VIC model to explore the change trend of water resources in the Huaihe River Basin under global warming. These studies enable the accurate prediction of the available surface water.

Based on the prediction of available surface water corresponding to different climate change scenarios, regional water resources can be planned through optimization techniques. Li et al. (2015) developed the two-level linear fractional water management (TLFWM) model and the stochastic two-level linear fractional chance-constrained water management (STLFCWM) model to identify desired water resources management policies considering various uncertainties. Hu et al.

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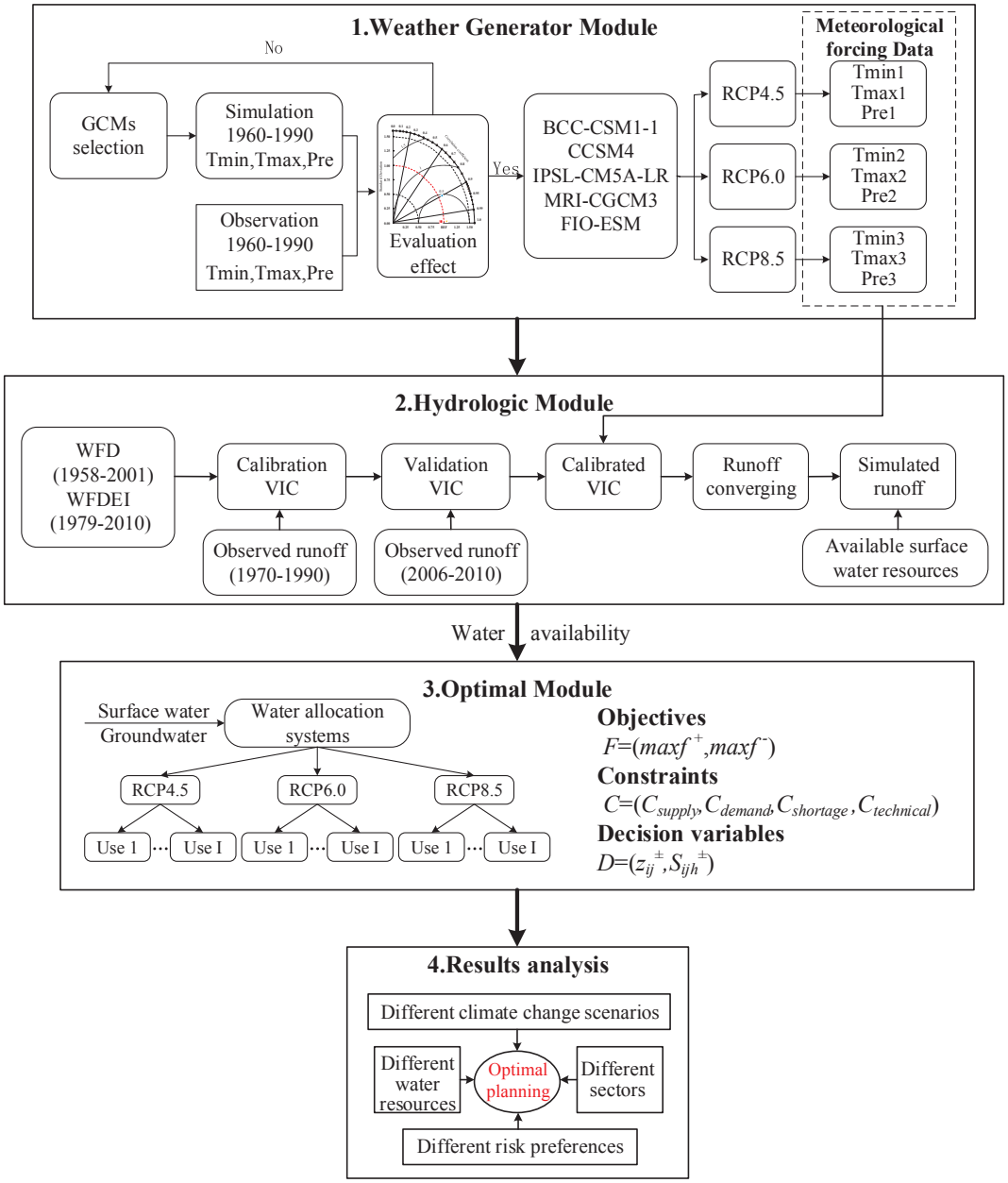

Fig. 1. Decision procedure of the developed framework for water resources planning.

(2016a) used the compromise programming (CP) method to trade off economic benefit efficiency and equity in the water allocation. Li et al. (2017) developed an intuitionistic fuzzy multi-objective non-linear programming (IFMONLP) model that solved multiple problems, including crop yield increases, blue water savings, and water supply cost reductions. However, there are many uncertainties, such as water availability variations, water price fluctuations, and allocation target changes, in regional water systems. Therefore, incorporating uncertainty programming methods into the optimization models for regional water allocation is necessary (Maqsood et al., 2005). The interval two-stage stochastic programming (ITSP) model is widely used in many uncertainty optimization models (Lin et al., 2009; Lu et al., 2009). The ITSP model can overcome the complexity and uncertainty of water resource systems by using interval parameters and probability distribution, such as unit product income, upstream water quantity and changes in ecological water demand in different sectors, these uncertainties can lead to multiple uncertainties and uncertain amplifications via their interaction (Fu et al., 2018b). In summary, to ensure the sustainable development of water resources and improve their utilization rate, the ITSP model can optimally plan the allocation of water resource systems.

Because water shortages are exacerbated by climate change, the allocation risks should be considered in water allocations to ensure the coordinated development of the regional economy and water resources (Shao et al., 2011). Wang et al., 2017a integrated conditional value-at-risk (CVaR) into factorial stochastic programming to solve the random uncertainties and interactions in water resource systems. Hu et al. (2016b) used CVaR to control the risk of economic efficiency loss corresponding to variations in water availability. CVaR, which is an improved value-at-risk (VaR) method, is an investment risk measurement method (Rockfellar 2000) and is effectively used in optimization models for regional water allocation because it is based on a simple calculation and it provides a better reflection of potential risks (Xu and Yu, 2014; Yamout et al., 2007). Further, using CVaR can ensure fair water allocations and balance the system benefits and expected losses. Accordingly, incorporating CVaR into the ITSP model is useful for

analysing the fairness of water resources allocation. Unfortunately, using such an integrated model to plan regional water resources based on water balance simulations under different climate change scenarios has been limited thus far.

Therefore, it is significant to integrate the water availability prediction results and the CVaR model in a water allocation optimization model; however, a limited number of studies have reported such an integration. This paper aims to plan regional water allocations under different RCP scenarios using an interval parameter CVaR two-stage stochastic programming model. The proposed approach is capable of (1) alleviating the imbalance between water supply and demand through the conjunctive use of surface water and groundwater; (2) promoting the economic benefits of the water resource system while simultaneously considering the penalties and risks due to violated policies; (3) reflecting uncertainties expressed as discrete intervals and probability distributions; and (4) obtaining various water planning alternatives under different climate change scenarios.

2. Problem description

2.1. Overview of the problem

In the past studies on the optimal allocation of water resources, the available water resource is usually derived from the planning report. To provide a credible water resources allocation plan for decision makers, the available water prediction is very important. With the RCP and GCMs employed to predict temperature and precipitation under various climate change scenarios, a VIC model was used to simulate the water balance, and a simulated runoff was obtained. To ensure the ecological sustainability of the river basin, a 70% runoff volume is needed to meet the ecological water demand in the basin. Then, the remaining 30% is used as the available surface water that combines with groundwater allocated to the municipal, industrial and agricultural sectors in the basin. CVaR is introduced into the water allocation model to ensure fair water allocation. The decision procedure of the developed framework for water resources planning is illustrated in Fig. 1. The framework includes three modules: (1) the weather generator module that generates the future climatic conditions under various RCP scenarios by GCMs, (2) the hydrologic module that uses the VIC model to simulate and predict the runoff volume, and (3) the optimization module that obtains the operating rules for the best economic effect using the interval parameter CVaR two-stage stochastic programming model. Additionally, in step (4), the results analysis and a discussion according to the different scenarios are included.

2.2. Motivation for water resources allocation under the prediction of the available water

The fluctuation in the available water of the river basin causes great difficulties for water allocation. Different runoff volumes under different climate change scenarios can be obtained, and the allocation of water resources can serve as a reference for decision makers, therefore, reliable weather generator selection is necessary. The IPCC Fifth Assessment Report (AR5) is a comprehensive assessment of the various GCMs of the current Coupled Model Intercomparison Project Phase in the fifth phase (CMIP5). Based on the performance of these GCMs in China (Wang et al., 2017b) and the detailed comparison of GCMs presented by Yan et al. (2015), the ability of each GCM to simulate different variables is different. Pierce et al. (2008) reported that a multimodel combined average is superior to the estimate given by any one individual model. The present paper selected five GCMs that are suitable for the study area to comprehensively predict the climate, as shown in Table 1. This paper only considers the RCP8.5, RCP6.0, and RCP4.5 scenarios. Combined with the 5 GCMs, the temperature and precipitation data under each RCP scenario are obtained, which lay the foundation for the next research.

Table 1
CMIP5 GCMs used in this paper.

Model	Resolution	Institution	Country
BCC-CSM1-1	128 × 64	Beijing Climate Center, China Meteorological Administration	China
CCSM4	288 × 192	National Center for Atmospheric Research	USA
IPSL-CM5A-LR	96 × 96	Institute Pierre Simon Laplace	France
MRI-CGCM3	320 × 160	Meteorological Research Institute	Japan
FIO-ESM	128 × 64	The First Institute of Oceanography, State Oceanic Administration	China

Among the various methods, the VIC model, a macro-scale distributed hydrologic model originally developed by Liang et al. (1994), is widely used for runoff prediction. The VIC model has some significant characteristics in that the hydrologic cycle process, the water balance and the energy balance can be considered simultaneously along with the parameterization of the two runoff components of surface runoff and base flow. This model is widely used to study the impact of climate change on river flows (Zhai and Tao 2017; Xie et al., 2003; Lohmann et al., 1998). The prediction results of the five GCMs under the three RCP scenarios were coupled with the VIC model to predict the runoff change trends in the study area in 2050. To verify the reliability of the model, this paper used Taylor diagrams to validate the monthly maximum temperature, minimum temperature and precipitation from 1961 to 1990 (Section 4.3.1).

The Nash-Sutcliffe efficiency (NSE) coefficient and normalized root-mean-square deviation (NRMSD) were used in the calibration. The NSE is an indicator that is widely used to evaluate the performance of the hydrological model. The formula is as follows:

$$NSE = 1-\frac{\sum_{t=1}^{T}(Q_0^t-Q_m^t)^2}{\sum_{t=1}^{T}(Q_0^t-\overline{Q_0})^2} \quad (1)$$

where Q_0^t is the observed runoff volume at moment t, 10^8 m^3; Q_m^t is the simulated runoff volume at moment t, 10^8 m^3; and $\overline{Q_0}$ is the average observed runoff volume, 10^8 m^3. The value of NSE ranges from $-\infty$ to 1. A value of NSE of 1 indicates that the simulation result is perfect with high reliability. A value of NSE close to 0 indicates that the simulation result is close to the average observation result, that is, the overall result is credible but with a large simulation error. When the value of NSE is far less than 0, then the model is not credible.

The NRMSD indicates the standard deviation of the differences between simulations and observations (Lombard et al., 2009). This variable is calculated as follows:

$$NRMSD = \frac{\sqrt{\sum_{t=1}^{N}(Q_0^t-Q_m^t)^2/N}}{Q_{\max}-Q_{\min}} \quad (2)$$

where $Q_{\max}$ is the maximum observed runoff volume, 10^8 m^3, and $Q_{\min}$ is the minimum observed runoff volume, 10^8 m^3. Consequently, the VIC model can simulate the reliable runoff volume to provide a basis to obtain the available surface water.

2.3. Coping with risk resulting from inequity

For different sectors, the economic benefits produced by each water supply unit are quite different, likely leading to an unfair allocation of water resources. Generally, the risk is proportional to the return such that more water allocation to the industrial sector results in greater economic benefits, however, the competition for water becomes more pronounced among the sectors, leading to a higher risk of water system failure. Therefore, managing the inequity of water allocation is very important. To prevent an unequal water allocation, CVaR, which can better balance the conflict between system benefits and system risk, is integrated to obtain a more reasonable and effective water allocation

scheme. The formula of CVaR is as follows:

$$\min_{x\in X}[E(f(x,\omega)) + \lambda\rho(q(x,\zeta(\omega)))] \tag{3}$$

where x is the decision variable; ω is a random variable; $E(f(x,\omega))$ is the value of the expected return function; λ ($\lambda \in [0,1]$) is the non-negative weight coefficient or risk coefficient to trade off the expected penalty with risk, which is determined by the risk preferences of the decision makers, thus resulting in different optimization solutions; ρ is a risk measurement model; q is a continuous loss function; and $\zeta(\omega)$ is a random function. The conditional value-at-risk of random variables at confidence level $\alpha(\alpha \in [0,1])$ can be defined as follows (Fu et al., 2017):

$$\rho = \lambda\left[\eta + \frac{1}{1-\alpha}E(p_h v_h^{\pm})\right] \tag{4}$$

where η is the maximum loss of the system under a given t confidence level, and α is the confidence level, usually set to 0.90, 0.95, or 0.99 (Qiu et al., 2014). This paper selects $\alpha = 0.95$ for the results to facilitate the calculation. v_h is a positive auxiliary variable. Obviously, with CVaR the decision makers can achieve a more reasonable water allocation scheme.

3. Modelling

3.1. Notation

An interval parameter CVaR two-stage stochastic programming model for regional water allocation is developed in this part. To present the model, a list of notations is provided in Table 2.

3.2. Objective functions

The purpose of optimizing water resources allocation is to determine how much water from different water sources can be used to meet the water demands of each sector and maximize the system benefits. In water resources allocation systems, the total water supply is the sum of the water supply amount of each sector; however, the water supply of each sector varies with time, and the future available water is uncertain. Therefore, it is necessary to forecast the water supply for each sector based on the historical data of the water supply and the regional economic development plans. Then, the predicted water demand can be regarded as the water supply target. If the actual water supply to each sector meets the corresponding water target, then the ideal system benefits can be obtained. If the actual water supply to each sector does not satisfy the target, then a water shortage will occur, consequently generating a water shortage penalty that will reduce the system benefits. To express the uncertainty of the water supply target, the per unit water supply benefits, the penalty coefficient, and the interval parameter can be introduced to solve the problem. Therefore, the ITSP model is adopted in this paper. The objective function of the model is to maximize the system benefits subject to a series of constraints associated with water resources, such as the available water, water demand, and water shortage constraints. According to the principle of the ITSP model, the first stage of the model is to allocate water (i.e., the water target) to different sectors under different RCP scenarios, directly leading to various water resource availabilities; the second stage will be composed of the sectors to calculate the loss of benefits resulting from water shortage. The ITSP model can be expressed as follows:

$$max\, f^{\pm} = \sum_{i=1}^{I}\sum_{j=1}^{J} B_{ij}^{\pm}W_{ij}^{\pm} - E\left(\sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{\pm}S_{ijh}^{\pm}\right) \tag{5}$$

where "+" indicates the upper limit of the parameter and "−" indicates the lower limit of the parameter. The water deficits of different RCP scenarios in the target year are treated as discrete functions. Therefore, the interval two-stage stochastic programming model can be expressed as follows:

$$max\, f^{\pm} = \sum_{i=1}^{I}\sum_{j=1}^{J} B_{ij}^{\pm}W_{ij}^{\pm} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H} p_h C_{ij}^{\pm}S_{ijh}^{\pm} \tag{6}$$

With the integration of the ITSP and CVaR models, an interval parameter CVaR two-stage stochastic programming model can be formulated and expressed as follows:

Objective function

$$max\, f^{\pm} = \sum_{i=1}^{I}\sum_{j=1}^{J} B_{ij}^{\pm}W_{ij}^{\pm} - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H} p_h C_{ij}^{\pm}S_{ijh}^{\pm} - \lambda\left(\eta + \frac{1}{1-\alpha}\sum_{h=1}^{H} p_h v_h^{\pm}\right) \tag{7}$$

3.3. Constraints

(1) Available water constraints

The availability of water for sectors is limited. The available surface water for each sector must not exceed the total available water. This constraint can be expressed as:

$$Q_{ijh}^{\pm} \geqslant W_{ij}^{\pm} - S_{ijh}^{\pm} \tag{8}$$

(2) Water demand constraints

To ensure basic use and development, the minimum water demand for each sector should be satisfied. Meanwhile, the water allocated to each sector should be no more than its maximum expected volume to avoid waste and improve water use efficiency. This constraint can be expressed as:

$$W_{ij\,\max} \geqslant W_{ij}^{\pm} \geqslant W_{ij\,\min} \tag{9}$$

(3) Water shortage constraints

The volume of the water shortage in each sector should be less than the volume of the water requirement during all water allocation stages. This constraint can be expressed as:

$$S_{ijh}^{\pm} \leqslant W_{ij}^{\pm} \tag{10}$$

(4) Technical constraints

To consider the balance between the system benefits and the system risk, CVaR constraints are required, as follows:

Table 2
Definitions of symbols used in the model.

Indices	Definition
i	Index of sector
j	Index of water sources
h	Index of scenarios
max	Superscript for maximum
min	Superscript for minimum
Decision variables	
$W_{ij}^{\pm}$	Water supply target (m^3)
$S_{ijh}^{\pm}$	Water shortage amount in the target year 2050 (m^3)
Parameters	
B_{ij}	Per unit water supply benefits (yuan/m^3)
C_{ij}	Unit water shortage penalties (yuan/m^3)
p_h	The occurrence probability of different scenarios, $\sum_{h=1}^{H} p_h = 1$
$W_{ij\,\max}$	Maximum water demand targets (m^3)
$W_{ij\,\min}$	Minimum water demand targets (m^3)
Random parameters	
Q_{ijh}	The available water from surface water and groundwater (m^3) Obtained by VIC simulation results

Note: yuan is a Chinese currency unit.

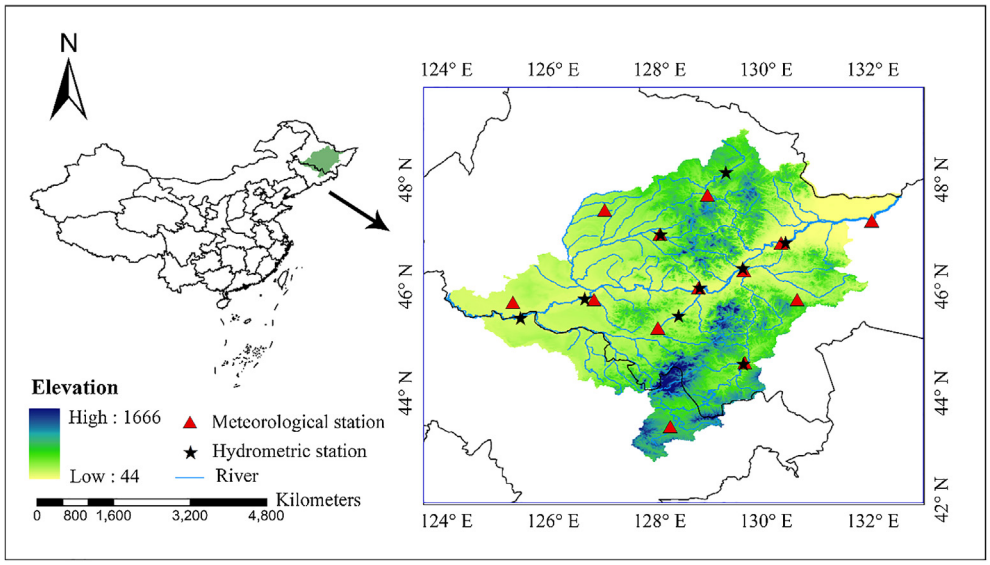

Fig. 2. Location and meteorological stations of the Lower Songhua River Basin in northeast China.

$$v_h^{\pm} \geqslant \sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{\pm} S_{ijh}^{\pm} - \eta \tag{11}$$

(5) Non-negative constraints

The water allocated to the study area from the surface water and groundwater should not be negative. This constraint can be expressed as:

$$S_{ijh}^{\pm} \geqslant 0 \tag{12}$$

$$v_h^{\pm} \geqslant 0 \tag{13}$$

$$\eta \geqslant 0 \tag{14}$$

In this model, $W_{ij}^{\pm}$ is an uncertain parameter in the form of an interval number that cannot be solved directly through the interval algorithm. Therefore, according to Zhang et al. (2009), decision variables z_{ij} ($z_{ij} \in [0, 1]$) are introduced to solve the model. Then, the interval parameter $W_{ij}^{\pm}$ can be converted to a deterministic parameter. Let $W_{ij}^{\pm} = W_{ij}^{-} + \Delta W_{ij} z_{ij}$ and $\Delta W_{ij} = W_{ij}^{+} - W_{ij}^{-}$; when $z_{ij} = 0$, $W_{ij}^{\pm}$ equals the lower limit of the interval, while when $z_{ij} = 1$, $W_{ij}^{\pm}$ equals the upper limit of the interval. Finding the optimal solution of decision variables z_{ijopt} enables the optimal solution of $W_{ij}^{\pm}$ to be obtained as follows: $W_{ijopt}^{\pm} = W_{ij}^{-} + \Delta W_{ij} z_{ijopt}$.

3.4. Global model

Combing the interval algorithm, the above formulas (7)–(14) can be transformed into two deterministic submodels. Since the objective function seeks the maximum system benefits, the upper bound of the submodel is solved first as follows:

$$max\, f^{+} = \sum_{i=1}^{I}\sum_{j=1}^{J} B_{ij}^{+}(W_{ij}^{-} + \Delta W_{ij} z_{ij}) - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H} p_h C_{ij}^{-} S_{ijh}^{-} - \lambda\left(\eta + \frac{1}{1-\alpha}\sum_{h=1}^{H} p_h v_h\right) \tag{15}$$

$$Q_{ijh}^{+} \geqslant W_{ij}^{-} + \Delta W_{ij} z_{ij} - S_{ijh}^{-} \tag{16}$$

$$W_{ij\max} \geqslant W_{ij}^{-} + \Delta W_{ij} z_{ij} \geqslant W_{ij\max} \tag{17}$$

$$S_{ijh}^{-} \leqslant W_{ij}^{-} + \Delta W_{ij} z_{ij} \tag{18}$$

$$v_h \geqslant \sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{-} S_{ijh}^{-} - \eta \tag{19}$$

$$S_{ijh}^{-} \geqslant 0 \tag{20}$$

$$v_h \geqslant 0 \tag{21}$$

$$\eta \geqslant 0 \tag{22}$$

The variables z_{ij} and S_{ijh}^{+} are decision variables, and z_{ijopt}, S_{ijhopt}^{+}, and f_{opt}^{+} are solutions of the upper bound of the submodel. Then, $W_{ijopt}^{\pm}$ can be obtained based on z_{ijopt}. In the same way, the lower bound of the submodel is expressed as follows:

$$max\, f^{-} = \sum_{i=1}^{I}\sum_{j=1}^{J} B_{ij}^{-}(W_{ij}^{-} + \Delta W_{ij} z_{ijopt}) - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{h=1}^{H} p_h C_{ij}^{+} S_{ijh}^{+} - \lambda\left(\eta + \frac{1}{1-\alpha}\sum_{h=1}^{H} p_h v_h\right) \tag{23}$$

Constraint conditions:

$$Q_{ijh}^{-} \geqslant W_{ij}^{-} + \Delta W_{ij} z_{ijopt} - S_{ijh}^{+} \tag{24}$$

$$W_{ij\max} \geqslant W_{ij}^{-} + \Delta W_{ij} z_{ijopt} \geqslant W_{ij\min} \tag{25}$$

$$S_{ijh}^{+} \leqslant W_{ij}^{-} + \Delta W_{ij} z_{ijopt} \tag{26}$$

$$v_h \geqslant \sum_{i=1}^{I}\sum_{j=1}^{J} C_{ij}^{+} S_{ijh}^{+} - \eta \tag{27}$$

$$S_{ijh}^{+} \geqslant S_{ijhopt}^{-} \geqslant 0 \tag{28}$$

$$v_h \geqslant 0 \tag{29}$$

S_{ijopt}^{-}, f_{opt}^{-} can be obtained by solving the lower bound of the submodel. Thus, the optimal solutions of the interval parameter CVaR two-stage stochastic programming model are $f_{opt}^{\pm} = [f_{opt}^{-}, f_{opt}^{+}]$, $S_{ijhopt}^{\pm} = [S_{ijhopt}^{-}, S_{ijhopt}^{+}]$, and the optimal water allocation amount can be calculated by $OPT_{ij}^{\pm} = W_{ijopt}^{\pm} - S_{ijopt}^{\pm}$.

4. Case study

4.1. Study area

The study area is the Lower Songhua River Basin, which is located in

northeast China (124.04° to 132.52°E and 42.72° to 48.96°N, Fig. 2); this basin is an important commodity grain production base. The Nenjiang River and the upper Songhua River flow into the Lower Songhua River. The main stream of the Lower Songhua River travels a total distance of 939 km and drains an area of 184,600 km^2, and the average annual precipitation of this area is 591.6 mm. The multiannual average volumes of surface water and groundwater are 35.968 billion m^3 and 13.611 billion m^3, respectively. Historically, the utilization rate of transit water resources in the study area has remained at approximately 30%, and these are the main water resources for production and livelihood in the basin. To promote the steady development of the social economy in the river region, an adequate water supply for municipal, industrial and agricultural sectors should be provided. The annual temperature range in this area is from −25.83 °C to 26.5 °C, so the main water inflow is concentrated from June to September due to the long frost period. Hence, to meet the requirements of the ecological water demand of the river and to meet the increasing demand for water in each water sector, it is necessary to reasonably allocate water resources and to solve the competing interests of the water sectors in the Lower Songhua River Basin.

4.2. Data collection

Long-term hydrological and meteorological data are critical for predicting river flow trends. Climate change (mainly precipitation and temperature) significantly affects the volume of runoff in the study area. Considering the availability of data, 5 hydrometric stations on the main stream, 4 hydrometric stations on the tributaries, and 13 national meteorological stations in the Lower Songhua River Basin are selected to collect monthly runoff volume, precipitation and temperature data from 1961 to 1990, which can be used for testing the model performance. The runoff volume data of the above hydrometric stations are from the hydrographic office in Heilongjiang Province, China. The information regarding the meteorological stations is from the China Meteorological Data Service Center (CMDC). Table 3 provides basic information regarding the 10 hydrometric stations. The amounts of groundwater and the water supply targets are obtained from the Songliao Water Resources Bulletin (2001–2015), the Heilongjiang almanacs, the statistical almanacs of Heilongjiang Province, and field research data. WATCH Forcing Data (WFD) (1958–2001) and WATCH Forcing Data ERA Interim (WFDEI) (1979–2010) downloaded from http://www.eu-watch.org/ are used to calibrate and validate the VIC model because they are specifically designed to drive land surface models and hydrological models (Weedon et al., 2011; Weedon et al., 2015). Yan et al. (2015) previously verified the accuracy and reliability of the WFD and WFDEI data.

4.3. Results analysis

4.3.1. Temperature and precipitation simulation

To verify the simulation accuracy of the maximum temperature (Tmax), minimum temperature (Tmin), and precipitation (Pre) under the selected five GCM scenarios in the study area, this paper first used the GCMs shown in Fig. 3 to simulate the Tmax, Tmin and Pre of the years 1961–1990 with a resolution of 0.5° × 0.5°. Then, the data were extracted and sorted using ArcGIS, and the annual monthly average values of Tmax, Tmin and Pre of the study area were obtained. The simulated results were compared and verified with the monthly average values of the corresponding meteorological elements obtained from the selected 13 national meteorological stations (see Fig. 2) from 1961 to 1990. The simulation results are shown in Fig. 3. Fig. 3(a) shows the comparison between the simulated data and the measured data. The simulation results and the measured values of Tmax and Tmin are relatively consistent. For Pre, the simulated values coincide with the measured data in the dry season because there was less precipitation in the dry season, there was a long frost period in the dry season, and the precipitation changes over the 30-year period were relatively stable. However, for the Pre in the flood season, the simulation results are higher than the measured data, especially in July. The main reason for this finding is that there is remarkable variation in the precipitation amounts in the flood season over the study period, and the changes are irregular. The D-value between the measured maximum and minimum precipitation values in July of 1961–1990 was 426.2 mm. Fig. 3(b) is a Taylor diagram that can quantify the correspondence ratio between the simulation results and the measured data, including the Pearson correlation coefficient, the root-mean-square error (RMSE) and the standard deviation. As seen from the diagram, the Pearson correlation coefficients between the simulated values and the measured values of Tmax, Tmin and Pre are 0.994, 0.993 and 0.905, respectively. The RMSEs are 0.11, 0.12 and 0.49, respectively, and the standard deviations are 0.985, 1.003 and 1.063, respectively. The correspondence ratio between the simulation results and the measured data shows that the results of the GCM simulations are better. Therefore, the simulation outputs corresponding to the GCMs can provide meteorological driving data in 2050 for the VIC model.

4.3.2. Runoff volume simulation

Based on the simulated outputs of GCMs, this paper used VIC to simulate the water balance of the study area. The volumes of runoff on each grid were output by running the VIC. Then, the runoff on each grid was collected in the outlet section of the river basin by coupling with the concentration model. To tailor the model to the study area, it was necessary to calibrate and validate the VIC model by using the WFD (1958–2001) and WFDEI (1979–2012). After the VIC model was calibrated, it was evaluated using the measured runoff volume data from 2006 to 2010. Taking two hydrometric stations on the main stream of the Songhua River as an example (i.e., the Jiamusi and Harbin stations), the verification results of the simulated and measured annual runoff volume data and average monthly runoff volume data for many years are shown in Fig. 4. From the overall verification conditions of the two hydrological stations, the simulated runoff volume obtained by the VIC was relatively high. The simulated runoff volume during the dry season was relatively accurate, while during the flood season, the simulation values were higher than the average monthly values. The main reason

Table 3
Detailed information of 10 hydrometric stations.

River	Hydrometric stations	Catchment area (km^2)	Annual precipitation (mm)	Annual mean Temperature (°C)	Annual runoff depth (mm)
Songhua River	Xiadaiji	363,923	587.24	4.12	116.73
Songhua River	Harbin	389,769	519.58	3.78	123.85
Songhua River	Tonghe	450,077	586.99	2.32	124.89
Songhua River	Yilan	491,706	545.77	3.23	116.73
Songhua River	Jiamusi	528,277	510.53	3.14	143.46
Hulan River	Tieli	1838	503.23	3.75	342.14
Mayi River	Yanshou	5627	615.17	2.50	203.17
Mudan River	Mudanjiang	22,194	531.01	3.78	297.04
Tangwang River	Wuying	4160	638.44	0.74	279.29

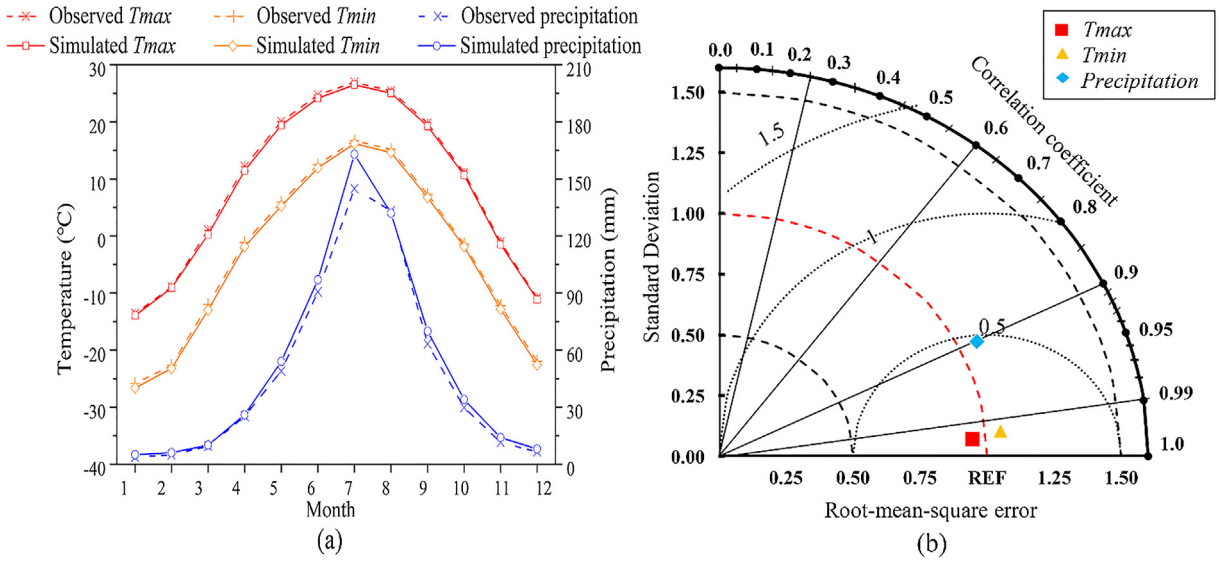

Fig. 3. Comparison of observed meteorological data and simulated meteorological data from 1960 to 1990.

for this result is that the VIC model took into account conditions with more floods in the Songhua River during the flood season, and these results were in accordance with the results of Zhai and Tao (2017). The NSE and the NRMSD of Jiamusi were 0.79 and 0.073, respectively. The NSE and the NRMSD of Harbin were 0.67 and 0.077, respectively. These results showed that the model performance was relatively stable and that the simulated runoff volume could be used in the subsequent water resources planning.

The calibrated VIC model was used to simulate runoff volume under different RCP scenarios. The corresponding results are illustrated in Fig. 5. As shown in the figure, the runoff volume will decrease to different extents under different scenarios in the future, and the trend of the future runoff volume will decrease. Under the RCP4.5 scenario, the predicted runoff volume and the historical runoff volume mostly overlapped, and these occasions mainly occurred in the dry season. The predicted runoff volume during the flood season was slightly lower than the historical runoff volume, but the overall trend was relatively consistent. Under the RCP6.0 scenario, the extreme range of the predicted runoff volume was reduced relative to the RCP4.5 scenario, and the predicted runoff volume exceeded the historical runoff volume only from January to March, while in the remaining months, the predicted runoff volume was lower than the historical volume. Under the RCP8.5 scenario, the predicted runoff volume peaked during the spring floods, indicating that climate warming had a significant effect on the melting rate of snow, which caused a sharp increase in runoff volume.

4.3.3. Optimal water allocation results

The predicted runoff volumes under RCP4.5, RCP6.0 and RCP8.5 were obtained based on the VIC. According to the P-III curve, the occurrence probabilities of the three scenarios were 0.3, 0.5 and 0.2, respectively. To address the problem in which the predicted runoff volume from the VIC model is high, this paper employed the correction method proposed by Zhai and Tao (2017). Considering the actual situation of surface water utilized in the study area, the utilization factor of the runoff was determined, and the available surface water was obtained. Table 4 lists the upper and lower limits of the surface water and groundwater availabilities under different RCP scenarios.

In water resources planning, if the available water can satisfy the water targets of different sectors, then the economic benefits can be maximized. However, if the water targets are not satisfied, then a water shortage penalty will occur. Table 5 provides information on the maximum and minimum water targets for each sector, the unit water

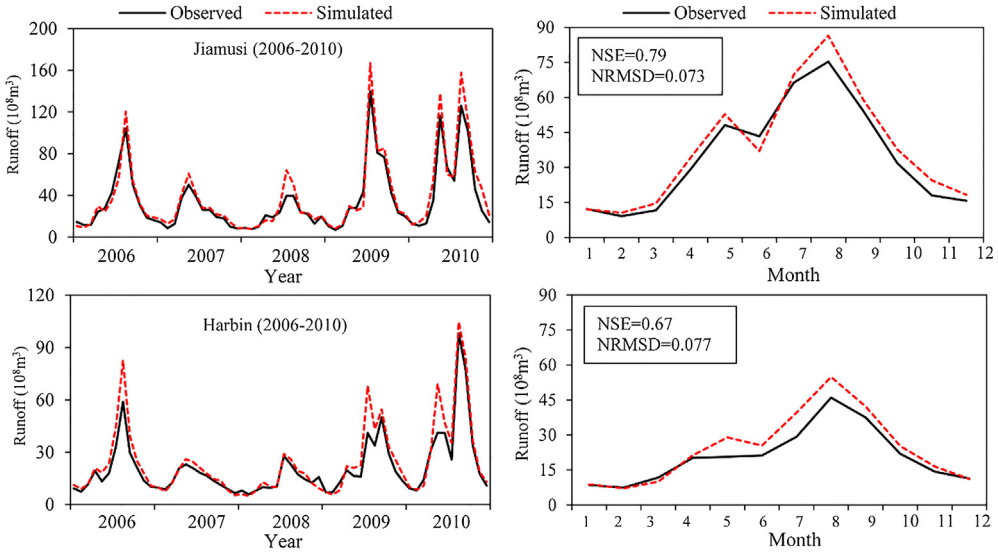

Fig. 4. Verification of simulated and measured runoff volume.

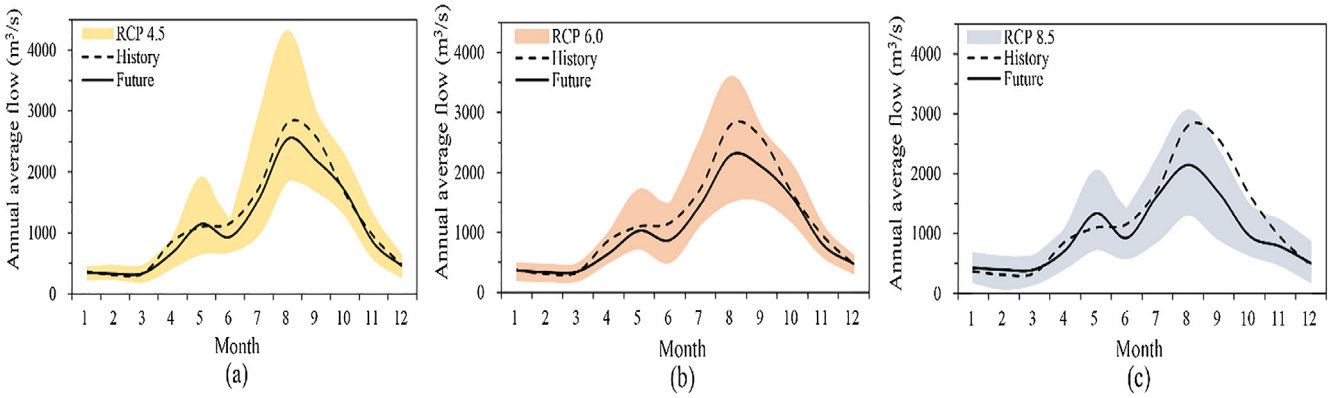

Fig. 5. Target year simulation of the annual average flow under different scenarios.

Table 4
Water resources availability under different RCP scenarios for different sectors.

Water demand sectors	Scenarios	Surface water ($10^8 m^3$)	Groundwater ($10^8 m^3$)	Occurrence probability
Municipal	RCP4.5	[7.14, 7.39]	[3.63, 3.80]	0.3
	RCP6.0	[6.23, 6.45]	[3.18, 3.38]	0.5
	RCP8.5	[5.27, 6.14]	[2.76, 3.02]	0.2
Industrial	RCP4.5	[9.02, 9.32]	[4.58, 4.79]	0.3
	RCP6.0	[7.86, 8.14]	[4.02, 4.27]	0.5
	RCP8.5	[6.66, 7.75]	[3.49, 3.81]	0.2
Agricultural	RCP4.5	[121.19, 125.28]	[61.59, 64.41]	0.3
	RCP6.0	[105.68, 109.40]	[54.04, 57.34]	0.5
	RCP8.5	[89.51, 104.11]	[46.93, 51.17]	0.2

Table 5
Basic data for water resources planning.

Water demand sectors	Water sources	Maximum water targets ($10^8 m^3$)	Minimum water targets ($10^8 m^3$)	Unit water supply benefits (yuan/m^3)	Unit water shortage penalties (yuan/m^3)
Municipal	Surface water	7.38	4.16	240	263
	Groundwater	3.60	1.33	210	294
Industrial	Surface water	30.47	17.10	220	236
	Groundwater	11.05	6.10	190	255
Agricultural	Surface water	135.84	105.59	180	194
	Groundwater	74.96	54.78	150	208

supply benefits and the unit water shortage penalties based on the research data of the study area and data from Rockfellar (2000).

The optimal water allocation results of the interval parameter CVaR two-stage stochastic programming model (i.e., formulas (15)–(29)) were obtained with the combined use of Matlab 2014 and Excel 2016. The optimal water targets of surface water and groundwater for different sectors can be obtained by $W_{ij}^{\pm} = W_{ij}^{-} + \Delta W_{ij} z_{ij}$. The amounts of water shortages under different RCP scenarios in the target years were calculated according to the upper and lower bounds of the submodels. The results are shown in Table 6.

(1) Combined utilization of surface water and groundwater
Considering the scarcity of groundwater and the high cost of exploitation, the allocation of water is mainly based on surface water and groundwater that is used as an auxiliary. The model regulates the overexploitation of groundwater in the study area, and the water supply of the municipal, industrial and agricultural sectors accounts for 32.48%, 26.29%, and 34.98% of the total water supply, respectively.

(2) The impact of water shortage penalties on the system economy
An increase in the water shortage leads to a reduction in the system economy. In the decision-making process, it is necessary to balance the degree of water shortage penalties among various water sectors and to improve the economic efficiency of the system as long as the basic constraints of the model are met. From the three water demand sectors, the agricultural sector needs the largest amount of water, and its optimal water supply target reaches 186.39×10^8 m^3; the water shortage is relatively high, but its water shortage penalty is relatively low. In addition, decision makers can arrange the scheduling of extraneous water in advance according to different water shortage levels.

(3) Solve the problem of the system uncertainty
By simulating the available water under different climate scenarios, the probability of different water flows is determined by the P-III curve, and the probability of the occurrence of the three scenarios is 0.3, 0.5, and 0.2. Historical data are used to help determine the range of parameters and then obtain the interval results. In short, the interval parameters, probability distribution and the amount of water inflow into the solution process are introduced to solve the system uncertainty problem.

(4) Water planning under different climate change scenarios
Under the RCP4.5 scenario, the supply for the municipal sectors fully meets the targets without a water shortage. Under the scenarios of RCP6.0 and RCP8.5, different degrees of water shortage occurred, and the RCP8.5 scenario experienced the most serious water shortage. From the water allocation results in Table 5, the impact of climate change on the water allocation problem cannot be ignored.

4.3.4. Risk analysis under different RCP scenarios

The objective function of the model was to maximize the system benefits. When $\lambda = 0$, the maximum system benefit, f_{opt}, is [31111.93, 33019.05] $\times 10^8$ yuan. In this situation, the CVaR was not considered in the process of solving the model; thus, the fairness of the water allocation was not considered. This paper analysed the changes in system benefits with changes in the risk coefficient λ ranging from 0 to 1, as shown in Fig. 6. Fig. 6 also shows that the economic benefit of the optimal water resources allocation in 2050 decreases as the value of λ increased. When $\lambda = 1$, the maximum benefit of the water resource system, f_{opt}, is [30868.22, 32442.64] $\times 10^8$ yuan.

The analysis of the above results shows that the solution of the model at $\lambda = 0$ reflects the characteristics of the ITSP model with the objective of maximizing the system benefits. Under water shortage conditions, the municipal sector had the greatest benefit, but the

Table 6
Optimal water resources allocation results for water demand sectors under different RCP scenarios.

Water demand sectors	Water sources	Scenarios	Occurrence probability	Optimal water supply target ($10^8 m^3$)	Water shortage ($10^8 m^3$)	Optimal allocation of water ($10^8 m^3$)	Decision variable
Municipal	Surface water	RCP4.5	0.3	7.15	0	7.15	0.928
		RCP6.0	0.5	7.15	[0.69–0.92]	[6.23–6.46]	0.928
		RCP8.5	0.2	7.15	[1.01–1.87]	[5.28–6.14]	0.928
	Groundwater	RCP4.5	0.3	3.44	0	3.44	0.928
		RCP6.0	0.5	3.44	[0.06–0.25]	[3.19–3.38]	0.928
		RCP8.5	0.2	3.44	[0.42–0.67]	[2.77–3.02]	0.928
Industrial	Surface water	RCP4.5	0.3	17.10	[7.78–8.08]	[9.02–9.32]	0
		RCP6.0	0.5	17.10	[8.96–9.23]	[7.87–8.14]	0
		RCP8.5	0.2	17.10	[9.35–10.44]	[6.66–7.75]	0
	Groundwater	RCP4.5	0.3	6.10	[1.31–1.51]	[4.59–4.79]	0
		RCP6.0	0.5	6.10	[1.83–2.08]	[4.02–4.27]	0
		RCP8.5	0.2	6.10	[2.29–2.60]	[3.50–3.81]	0
Agricultural	Surface water	RCP4.5	0.3	121.20	0	121.20	0.516
		RCP6.0	0.5	121.20	[11.79–15.52]	[105.68–109.41]	0.516
		RCP8.5	0.2	121.20	[17.09–31.69]	[89.51–104.11]	0.516
	Groundwater	RCP4.5	0.3	65.19	[0.78–3.60]	[61.59–64.41]	0.516
		RCP6.0	0.5	65.19	[7.85–11.15]	[54.04–57.34]	0.516
		RCP8.5	0.2	65.19	[14.02–18.26]	[46.93–51.17]	0.516

Maximum economic benefit [31111.93, 33019.05] $\times 10^8$yuan.

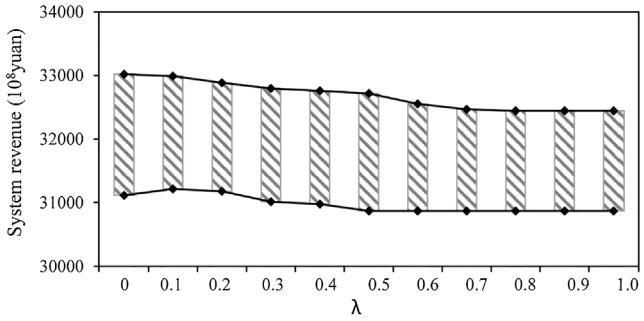

Fig. 6. Income of water resources systems under different levels of λ.

penalty was also the largest. The benefits and penalties produced by the industrial sectors were smaller, and those in the agricultural sector were the smallest. Hence, the model gave priority to satisfying the water targets of the municipal sector. This decision caused the largest water shortages and the most serious penalty to occur in the agricultural sector. This water allocation model did not achieve a fair allocation. By introducing the CVaR model into the ITSP model, the risk preference of water resources managers in water allocation planning can be considered, and with the increased level of risk aversion coefficient λ, the water allocation schemes seemed more conservative. The water supply to the municipal sector decreased, and the economic benefit decreased accordingly. The water supply to the agricultural sector increased as a result. However, the economic performance of the agricultural sector per unit water supply was lower than that of the municipal sector, and the overall economic benefit of the region still decreased. Considering CVaR in the model can help decision makers control the conflicts among different water sectors, select the appropriate optimization plans for water resources, regulate surface water and groundwater more reasonably and obtain sustainable economic benefits according to risk preferences and the water supply under different RCP scenarios.

5. Discussion

The total water supply in the target year is $220.18 \times 10^8 m^3$, and the multiannual average water supply is $231.79 \times 10^8 m^3$, saving a volume of $11.61 \times 10^8 m^3$ of water resources. Based on the results, the optimal water use structure can be obtained. The ratio of surface water to groundwater is close to 2:1. The ratio of surface water to groundwater of the multiannual mean is 1.62:1. Through model optimization, the utilization of surface water tends to increase, which has practical relevance for alleviating groundwater overexploitation in the study area. The total supply is $220.18 \times 10^8 m^3$ according to the model for the target year, while the multiannual average total water supply in the study area is $247.62 \times 10^8 m^3$. The total water supply is reduced by the model optimization, so the model also contributes to water savings. In summary, the framework developed in this paper can help the regions suffering from severe water shortages to save water and adjust the proportion of surface water and groundwater allocation (Table 7).

6. Conclusion

This study developed a framework that included the generation of climate change scenarios and water balance simulations based on the VIC model for regional water resources planning based on an interval parameter CVaR two-stage stochastic programming model. Moreover, the water planning for municipal, industrial and agricultural sectors under different scenarios was optimized in accordance with their penalties and benefits. The case study of the Lower Songhua River Basin revealed that the model was reasonable.

The following conclusions can be drawn: (1) The uncertainty of the system can be overcome by the framework. GCMs simulated the temperature and precipitation, and the VIC model accurately simulated the runoff; then, the amount of available water obtained under different RCP scenarios was more reliable. In addition, the interval parameters and probability distributions were used to further control the uncertainty of water resources in the model establishment. (2) The water shortage caused by competition was intensified among the water demand sectors. The result of water allocation in the agricultural sector was not obviously affected by the economic benefits of the unit water supply; the second stage of the model introduced a water shortage penalty function that can avoid this problem. (3) Introduction of the CVaR can guarantee the fairness and sustainability of water allocations by balancing the income risk between different water demand sectors.

Table 7
Surface water and groundwater utilization rate in the total water supply.

Water sources	RCP4.5	RCP6.0	RCP8.5	Multi-annual mean
Surface water	66.36%	66.17%	65.59%	61.81%
Groundwater	33.64%	33.83%	34.41%	38.19%

Decision makers can select the water allocation plans based on their risk preferences and the actual conditions.

The developed framework considering RCP scenarios is beneficial to optimally allocate regional water resources, especially for the regions suffering from severe water shortages and groundwater over-exploitation. However, multiple uncertainties exist in regional water planning, and the joint optimization of both water quality and quantity increases the complexity of regional water resources planning; thus, these topics deserve future study.

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